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Adrian Carro

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Could Spain be less different? Exploring the effects of macroprudential policy on the house price cycle†

Adrian Carro[a,b,*]

[a]*Financial Stability and Macroprudential Policy Department, Banco de España, Madrid, Spain*
[b]*Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK*

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Abstract

Employing an agent-based model of the Spanish housing market, this paper explores the main drivers behind the large amplitude of the Spanish house price cycle —as compared to most other European countries—, as well as the scope for macroprudential policy to reduce this amplitude. First, we exploit the availability of a previous calibration to the UK, characterised by a smaller house price cycle, to show the prominent role played by the distributions of various mortgage risk metrics: loan-to-value, loan-to-income and debt-service-to-income ratios. Second, we use the model to calibrate both a hard loan-to-value and a soft loan-to-income limit to smooth the Spanish house price cycle and match the amplitude of the UK equivalent. Finally, we characterise the effects of these calibrated policies over the different phases of the cycle, finding both instruments to reduce credit and price growth during the expansionary phase as well as to reduce their decline during the contractionary phase. Moreover, both instruments lead to a compositional shift in lending: the loan-to-value policy from first-time buyers to buy-to-let investors and the loan-to-income policy from both first-time buyers and home movers to buy-to-let investors.

Keywords: Agent-based modelling, housing market, macroprudential policy, borrower-based measures, buy-to-let sector

JEL: D1, D31, E58, G51, R21, R31

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*Corresponding author

Email address: adrian.carro@bde.es (Adrian Carro)

1. Introduction

Numerous empirical studies have emphasized the role played by house price fluctuations within the business cycle, uncovering a strong co-movement of housing prices with GDP, consumption, investment, hours worked, real wages and housing investment (Carroll et al., 2011; Claessens et al., 2012; Mian et al., 2013; Piazzesi and Schneider, 2016; Lambertini et al., 2017; Cerutti et al., 2017b). In particular, 9 out of 11 US recessions since 1985 have been preceded by a decline in housing investment (Leamer, 2015). More generally, downturns in real house prices have been shown to be useful leading indicators of economic recessions across a broad sample of countries (Haavio et al., 2014). Different theoretical channels have been proposed to rationalise the impact of the house price cycle on the broader economy. First, since housing is typically the single largest asset in households' balance sheet, fluctuations in house prices significantly affect household wealth and hence consumption (housing net worth channel, Mian and Sufi, 2011; Liu et al., 2016; Berger et al., 2018). Second, the transmission of shocks from housing to consumption can be amplified by endogenously emerging housing illiquidity during downturns (liquidity channel, Garriga and Hedlund, 2020). Third, housing is also an important source of collateral used by economic actors, whose borrowing capacity will thereby be affected by changing housing prices (collateral channel, Chaney et al., 2012; Liu et al., 2013; Bahaj et al., 2020). Finally, since both the construction and acquisition of real estate are generally characterised by high leverage, when the bubble bursts, the resulting deleveraging depresses business and household spending for a long time, leading to slower recoveries (deleveraging channel, Jordà et al., 2015, 2016).

For all these reasons, one of the main goals set for macroprudential policy after the Global Financial Crisis has been to moderate house price fluctuations (Cerutti et al., 2017a). Given the weight of the real estate sector in its economy, as well as the role this sector played during the Global Financial Crisis, Spain offers an excellent setting to explore the potential use of macroprudential policy to moderate the house price cycle. As shown in Figure 1, house price cycles in Spain have been stronger than in most other European countries, consistently ranking among the strongest since at least the 80s. This has been particularly the case during the most recent boom-bust cycle around the Global Financial Crisis, when only Ireland suffered a stronger price reversal and both Spain and Ireland experienced a boom and bust far exceeding the size of those observed in other European economies. Finally, exposures to the housing sector have traditionally been a key part of the bank-dominated Spanish financial system. For instance, at the peak of the most recent boom phase —right before the Global Financial Crisis— mortgages to households amounted to 65% of the GDP, while loans to real estate and construction firms amounted to a further 45% of the GDP, thereby leading to more than 100% of the GDP in direct exposures to the housing sector (Akin et al., 2014).

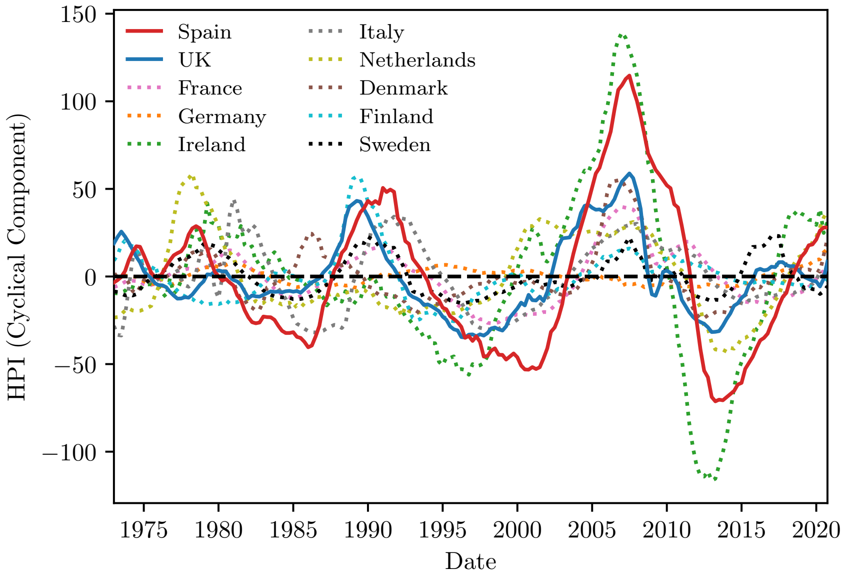

Figure 1: Cyclical component of the house price index (HPI) for various European countries. A Hodrick-Prescott filter with a smoothing parameter $\lambda = 129600$ has been applied to the data. Source: OECD real house price index data.

From a modelling perspective, housing markets are characterised by a number of challenges related to their highly heterogeneous nature. First, households interacting in housing markets are heterogeneous across multiple dimensions, such as their income, wealth and preferences, which strongly influence their decisions. Importantly, given its relevance in the cash flows of many households, housing can itself become a driver of further differences, for instance, regarding household wealth. Furthermore, when studying policy interventions, it would be hard to assess the effects of a given instrument on the various segments of the housing market, such as renters, first-time buyers, home movers or buy-to-let investors, unless these segments are explicitly considered, together with their characteristic dynamics. Second, housing is an extremely heterogeneous good, with houses differing in aspects such as their location, size, condition and dwelling type. Given this high degree of heterogeneity and the associated difficulty to assess and compare different properties, housing markets are fraught with information asymmetries. These factors, together with high transaction costs and long investment horizons, make housing a relatively illiquid asset and allow for imbalances between supply and demand to persist for much longer than in markets for more homogeneous products (Riddel, 2004). For instance, an excess in demand at a given location or for a certain type of dwelling cannot be easily counterbalanced by an excess in supply at a far away location or of a very different type of dwelling. Agent-based models are particularly well suited to meet these challenges and capture many of these features. In particular, they can easily incorporate large degrees of heterogeneity across multiple dimensions, they can explicitly capture local market interactions, they are capable of generating out-of-equilibrium dynamics and fully endogenous cycles, and they are flexible enough to simulate a great variety of policies (Farmer and Foley, 2009; Fagiolo and Roventini, 2017; Haldane and Turrell, 2018, 2019). Because of these characteristics, agent-based models are an ideal tool to study the emergence of systemic risks in housing markets.

In this paper, we use an agent-based model of the Spanish housing market to explore the main drivers behind the large amplitude of the Spanish house price cycle —as compared to most other European countries—, as well as to investigate the scope for macroprudential policy to reduce this amplitude. In particular, we adapt and calibrate to Spain a well-known agent-based model of the housing market originally developed for the UK (Baptista et al., 2016; Carro et al., 2022) and further applied to Denmark (Cokayne, 2019) and Italy (Catapano et al., 2021). This model includes life cycle dynamics, agent heterogeneity across multiple dimensions, heuristic (boundedly rational) rules of behaviour, adaptive expectations, both a sales and a rental market and a dynamic buy-to-let sector. Importantly, the dynamics of the model are characterised by the emergence of fully endogenous house price cycles, derived from the actions and interactions of the agents and not requiring any external input of shocks. First, noting the significantly smaller amplitude of the UK house price cycle as compared to the Spanish equivalent (see Figure 1), we exploit the availability of both calibrations —to the UK and to Spain— to explore which aspects of the Spanish calibration are behind the increased amplitude of its house price cycle. To this end, we build hybrid parameterisations, allowing us to assess the impact of specific parameters, small sets of parameters and particular mechanisms on the amplitude of the resulting cycles. In this way, we find that parameters and mechanisms related to lending standards and desired down-payments play a prominent role in generating the stronger Spanish cycles. Second, we use the model to calibrate both a hard loan-to-value (LTV) and a soft loan-to-income (LTI)[1] limit to smooth the Spanish house price cycle and match the amplitude of the UK equivalent. Interestingly, both calibrated limits are less restrictive than the corresponding UK distributions of lending standards would suggest. Finally, we characterise the effects of these calibrated policies over the cycle. In this sense, we find both instruments to reduce credit and price growth during the expansionary phase, as well as to reduce their decline during the contractionary phase. Importantly, both instruments lead to a compositional shift in lending towards buy-to-let investing: in the case of the LTV policy, credit shifts mostly from first-time buyers to buy-to-let investors, while in the case of the LTI policy, credit shifts from both first-time buyers and home-movers towards buy-to-let investors. This is due to the generally higher wealth and income of buy-to-let investors, who are thereby less constrained by these policies, combined with the fact that both policies make buy-to-let investing more attractive by reducing purchase prices while increasing the demand for rental accommodation.

The remainder of the paper is structured as follows. In Section 2 we briefly review the relevant literature and describe our main contributions. Section 3 provides a general overview of the model, leaving an in-depth description of the main model heuristics for Appendix A and a detailed account of the estimation and calibration of model parameters for Appendix B. In Section 4 we validate the model by comparing its output with Spanish data from various sources, including multiple distributions of mortgage and household micro-data as well as the time series of housing prices. The main results of our analysis are presented in Section 5, starting with an exploration of the main drivers behind the amplitude of the house price cycle in Subsection 5.1, continuing with two exercises to calibrate borrower-based macroprudential policies in Subsection 5.2 and finishing with an extensive analysis of the various effects of these calibrated policies on different distributions, types of households and over the different phases of the house price cycle in Subsection 5.3. Finally, Section 6 presents some concluding remarks about these results and the associated policy implications, as well as an outline of future research avenues.

[1] A soft limit allows for a certain fraction of new mortgages to exceed said limit.

2. Related Literature

This paper contributes to three main strands of literature. First, it is related to other contributions focusing on the Spanish housing market and its house price cycles. Estrada García and Saurina Salas (2016) provide a general description of the recent boom-bust cycle in Spain around the Global Financial Crisis, with a focus on macroprudential policy. Using granular data on mortgage loans in Spain, Akin et al. (2014) underline the role played by too soft lending standards and excessive risk-taking during the boom phase previous to the Global Financial Crisis. Martín et al. (2018) focus on a compositional shift in credit from non-housing to housing firms in the early years of the recent housing bubble in Spain, later on replaced by a shift in the opposite direction as housing firms paid back their initial loans. With respect to this strand of literature, this paper provides a closer look at the distributions of different mortgage risk metrics (loan-to-value, loan-to-income and debt-service-to-income ratios), as well as a model able to, on the one hand, reproduce such distributions and, on the other hand, display realistic house price cycles.

Second, the model presented here relates to a number of other (non-agent-based) models with a focus on the housing market and including different forms of borrowing constraints. For instance, in a seminal contribution Iacoviello (2005) introduces a business cycle model with housing as collateral, and thus with a borrowing constraint tied to housing prices. Rubio and Carrasco-Gallego (2016) develop a two-country version of this seminal paper and use it to study the impact of various shocks in the Euro area. Greenwald (2018) and Ingholt (2019) focus on comparing a debt-service-to-income limit with a loan-to-value limit. Using a life-cycle model with housing and both a loan-to-value and loan-to-income limit, Paz-Pardo (2021) focuses on the impact of changes in earning dynamics on the reduction of home-ownership across generations. In the context of these contributions, our model represents an alternative approach, based on heuristic (boundedly rational) rules of behaviour and adaptive expectations, as well as including a high degree of household heterogeneity across multiple dimensions. Importantly, our approach displays fully endogenous house price cycles with realistic features, derived from the actions and interactions of the agents in the model and therefore not requiring any external input of shocks. Furthermore, our model includes a dynamic buy-to-let sector and rental market and shows a good match of the distributions of various mortgage risk metrics (loan-to-value, loan-to-income and debt-service-to-income ratios). As opposed to most contributions in this strand of literature, however, our model lacks a dynamic firm and production sector.

Third, our work is also related to a stream of papers developing agent-based models to represent different local and national housing markets initiated by Geanakoplos et al. (2012) and Axtell et al. (2014) with their model of the Washington DC housing market. Baptista et al. (2016) and Carro et al. (2022) build upon this original model by incorporating a life cycle dynamics, a fully-fledged buy-to-let sector together with an autonomous rental market, and a more realistic double auction market mechanism. They use this expanded model to study the impact of borrower-based macroprudential policy on the UK housing market. This first application of an agent-based model for the study of borrower-based macroprudential instruments sparked a series of related contributions by Mérő and Vágó (2018), Cokayne (2019), Laliotis et al. (2020), Catapano et al. (2021) and Tarne et al. (2021). With respect to this strand of literature, this paper contributes *(i)* a detailed calibration to Spain, *(ii)* a novel comparative exercise (hybrid parameterisations) exploiting the existence of multiple calibrations of the same model, *(iii)* a calibration exercise for the studied borrower-based instruments with a given amplitude of the house price cycle as a target, and *(iv)* an in-depth analysis of policy effects over the cycle.

3. Model overview

We build upon the agent-based model of the UK housing market developed by Baptista et al. (2016) and Carro et al. (2022). In particular, we introduce a series of modifications to adapt this original model to the Spanish housing market and we re-calibrate it using a breadth of (mostly micro-) data sources about Spain. As can be observed in the schematic diagram in Figure 2, the model has three main classes of agents: *(i)* households, *(ii)* a bank, and *(iii)* a Central Bank. Households interact with each other via the sales and the rental markets, i.e., by buying, selling, renting and letting out houses to each other. To buy houses, households can also interact with the bank by requesting a mortgage. In providing such mortgages, the bank applies its own internal lending standards in the form of loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) requirements. Finally, the Central Bank has the power to further regulate those lending standards in the form of borrower-based macroprudential policies, potentially imposing more constraining limits.

The following subsections provide a general outline of the model, leaving a detailed description

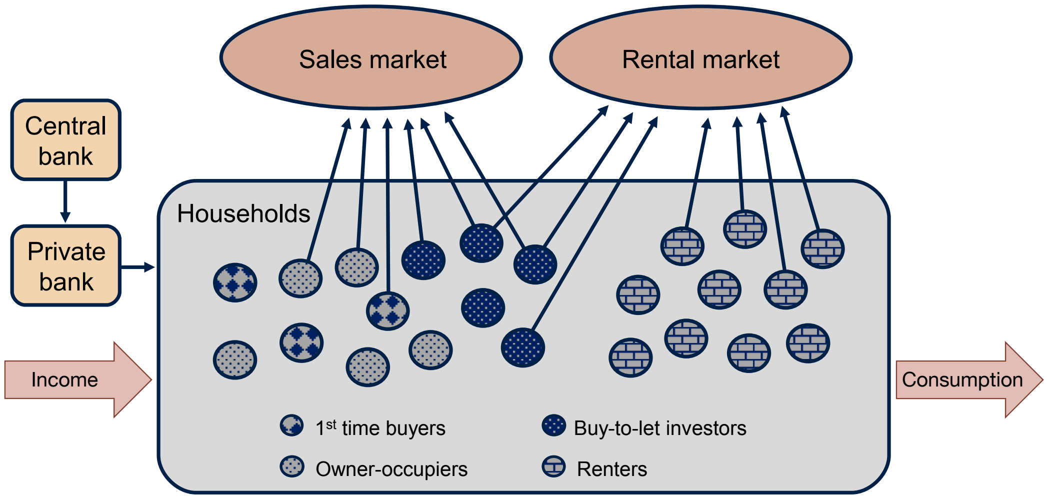

Figure 2: Diagram of the model. Schematic representation of the main agents and interactions in the model.

of the main (heuristic) rules of behaviour of its agents for Appendix A. In particular, Subsection 3.1 describes the initial setup of the model, Subsection 3.2 provides an overview of the simulation step and Subsection 3.3 describes the main differences between the model presented here and the original UK version. The values of all model parameters, as well as a description of the estimation or calibration procedures and of the data sources used, can be found in Appendix B. For a more in-depth description of the model, except for the modifications introduced here, we refer the reader to Carro et al. (2022).

3.1. Initial model setup

Every simulation starts by creating the desired number of households,[2] each of them with *(i)* an initial age, drawn from a distribution estimated from data;[3] *(ii)* a permanent income percentile, drawn from a uniform distribution; and *(iii)* a permanent propensity to save, also drawn from a uniform distribution. Derived from these basic attributes, households are also assigned an initial income, dependent on the household's initial age and its income percentile, and an initial financial wealth, dependent on the household's initial income and its propensity to save. While both

[2] In order to adequately explore the parameter space during the calibration process, with the associated computational cost, we restrict ourselves to 10,000 households for all results to be presented here. In any case, we have confirmed the robustness of our main results with a reduced number of simulations with up to two million households.

[3] This is thought as representing the age of the Household Reference Person, a concept used in a number of surveys and usually understood to be the person within the household with the highest income.

income percentile and propensity to save remain fixed throughout the life of the household, its age evolves in time, driving the evolution of other household attributes, such as its actual income and desired financial wealth. Furthermore, with a probability dependent on their income percentile as estimated from data, some households are assigned a buy-to-let flag, allowing them to invest in buy-to-let properties.[4] These households are further divided into three different investor types depending on the relative importance they place on capital gains as opposed to rental yield. Specifically, we consider capital-gains-driven households, rental-income-driven households and mixed type households, equally weighting both forms of yield. Finally, all newly created households are said to be in social housing, understood as a form of temporary, free of charge accommodation which households can always use while trying to find a house to rent or buy. Importantly, households never choose to be in social housing and they are only sent there if they fail to secure another form of accommodation.[5] Thus, it is a proxy for situations like homelessness, living with parents or living out of housing and other social benefits.

The required number of houses, corresponding to an estimated target ratio of houses to household, are also created at the beginning of each simulation. Each house is characterised by an integer-valued parameter representing its quality. This parameter serves as a proxy for all possible features making houses different and some more desirable than others, such as their location, size, condition or dwelling type. House qualities are assigned uniformly at random at the beginning of the simulation and remain fixed throughout. Thus, the housing stock is divided into approximately equally sized quality segments. This stock of houses, which is to remain constant throughout the simulation, is initially distributed at random among households. Importantly, this random initial distribution avoids imposing any correlation structure between income, financial wealth, home ownership and house quality. These correlations will instead endogenously emerge due to the dynamics of the model, that is, as a consequence of the decisions and interactions of its agents.

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[4] Note that, according to the data, this probability displays an increasing trend as a function of the income percentile, with a particularly strong slope in the upper quartile of the income distribution.

[5] For simplicity and in order to avoid modelling housing transaction chains —the coordinated and simultaneous sale and purchase of a number of properties linked in a chain—, households having sold their homes are also said to be temporarily in social housing while they look for a new home.

3.2. Overview of the simulation step

Once initialised, the model proceeds iteratively in discrete simulation steps of one month. In each of these time steps, the following model components are updated:

1. **Demographics:** New households are born, some households die and the rest of them age. We choose appropriate birth and death rates dependent on age so that both the total number of households and their distribution of age remain constant. As those created at the beginning of the simulation (see previous subsection), new households are born with all their characteristics —initial age, income percentile, propensity to save, initial income, initial financial wealth and, potentially, buy-to-let flag and investor type— drawn from suitable distributions. Moreover, they are initially set to live in social housing. When a household dies, all its financial and housing wealth is inherited by another randomly chosen household.

2. **Households:**

   (a) Receive income, pay housing expenses and consume: Households receive an exogenous monthly income, which is computed using a distribution of income conditional on age by evaluating the corresponding inverse cumulative function at the household's age and income percentile. Thus, as the household ages, its income changes, even though its income percentile remains fixed.[6] Then, households pay their housing expenses: Renters pay their monthly rent, and owners with a mortgage make their monthly mortgage payment.[7] Note that, as a consequence of rental payments, buy-to-let households with investment properties currently rented out will receive these payments as rental income. Finally, households spend on non-housing consumption depending on their remaining current financial wealth.

   (b) Make their housing decisions depending on their current housing status:

[6] Note that this fixed income percentile assumption effectively implies that we do not consider idiosyncratic shocks, such as unemployment.

[7] At this point, it is possible that a household cannot afford these payments. Since the nuances of bankruptcy dynamics are beyond the scope of our model, we directly consider these households as bankrupt and we artificially inject as much liquidity as necessary so that all scheduled payments are made, with no further action against the bankrupt household.

- If in social housing, they decide whether to rent or buy a new house.
- If renting, they always continue to rent until the end of their current rental contract, when they decide whether to find a new rental property or try to buy a house.
- If owner-occupying a house and not having the buy-to-let flag, they decide whether to sell this house.
- If owner-occupying a house and having the buy-to-let flag, they decide whether to buy a new investment property and, for each of their currently vacant investment properties, they decide whether to sell it.

Apart from this, house owners with unsuccessful offers left on the sales or rental market from previous months decide whether to lower the price of these offers.

(c) Place their bids and offers on the relevant market, whether sales or rental.

3. **Markets:** Both markets are cleared following a double auction mechanism, with the sales market being cleared first, followed by the rental market.[8] In particular, bids and offers are matched in a number of rounds, until no further match is possible. In each of these rounds, first, bidders are matched to the highest quality offer they can afford given their bid price. Then, offers with a single bid are directly cleared while for offers with multiple bids there is a certain probability of a price increase before selecting one of the bidders at random and clearing the transaction. Unsuccessful bids are removed from the market at the end of this process, while unsuccessful offers are kept for the following month.

4. **Bank:** There is a single bank in the model, representing the mortgage lending sector in the aggregate. This bank provides mortgages as requested by households, complying both with its internal lending standards as well as with any borrower-based macroprudential limits imposed by the Central Bank. Mortgages are effectively issued after market matching, when transactions are executed. However, at the stage when households are making their housing decisions, the bank provides each one of them considering a house purchase with a mortgage in principle letter setting out the conditions on offer and, specifically, the maximum principal available to each of them. At the end of the time step, the bank updates its mortgage interest

[8] In this way, buy-to-let investors acquiring a new investment property can directly offer it for rent within the same month.

rate for the next month, based on the rate for the current month and the resulting excess demand for credit over the bank's target.

3.3. Changes with respect to the original UK model

We provide in this subsection a detailed account of the differences between the model presented here and the original UK version as described in Carro et al. (2022). These differences are:

- **Taxes:** We have completely removed taxes from the model, both in the form of income taxes and National Insurance contributions. Given that we estimate and calibrate all other model parameters to be expressed in terms of gross income, as opposed to the net income used in the original model, this convenient simplification has virtually no effect on the results.
- **Government income support:** Since the measure of gross income that we use to estimate the exogenous income distribution for Spain already includes any government support received by the surveyed households, we have removed this mechanism and parameters as redundant for the Spanish calibration.
- **Essential consumption:** While the original model defines essential consumption as a fraction of the household's income, we define it instead as a minimum value of nominal consumption.
- **Expected rate of return on alternative non-housing investments:** As in the original model, we do not explicitly incorporate any alternative investment option apart from housing. However, we have introduced an exogenous expected rate of return on alternative non-housing investments, which buy-to-let investors in our model use to compare with the expected rate of return on the housing investments they consider, thereby moderating their demand for such housing investments when their expected rate of return is below the non-housing equivalent.
- **Buy-to-let desired down-payments:** In the original model, buy-to-let desired down-payments were set as drawn from an estimated normal distribution of down-payment fractions. On the contrary, we set these down-payments as drawn from an estimated log-normal distribution of nominal down-payments, the same functional form as used for the desired down-payments of first-time buyers and home movers, although with its own parameter val-

ues estimated from Spanish buy-to-let mortgage data. This design is closer to the observed (realised) distribution of down-payments.

- **Lending standards of the bank:** The hard loan-to-value (LTV) limit imposed by the bank in the original model has been replaced by a soft limit, thus allowing for a certain fraction of mortgages with LTV values over the limit. This allows the model to capture the double peak nature of the Spanish LTV distribution.[9]

- **Mortgages for buy-to-let investors:** As opposed to the original model, we do not consider interest-only mortgages for buy-to-let investors, but rather the same type of repayment mortgage product offered to owner-occupiers. Likewise, in our model, buy-to-let mortgages are subjected to the same loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) constraints as owner-occupying mortgages, in contrast to the LTV and interest-coverage-ratio constraints applied to buy-to-let mortgages in the original UK version. These changes are motivated by the fact that, as opposed to the UK equivalent, the Spanish mortgage market lacks a generally available mortgage product specific for buy-to-let investing. The only difference between these two types of mortgages in our model is that, while owner-occupying mortgages are to be fully repaid by a certain household age, it is enough for buy-to-let investors to apply for the mortgage before a certain age, the maturity offered being always the same. The main reason for this difference is that, as opposed to employment income, the stream of rental income from investment properties is not expected to decrease when the owner retires.

- **Home selling heuristics:** We have improved the rules used by households to decide whether to sell their homes by preventing them from selling if *(i)* given current market prices, their desired bid price and the maximum mortgage available to them, they would, in any case, decide to rent, or if *(ii)* given their current net wealth (including housing), moving house would lead to a decrease in house quality.

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[9] Actually, the results of the model are rather compared to the Spanish loan-to-price (LTP) distribution, as this is more reliable than the LTV distribution in the presence of a historical tendency to over-appraise the value of transacted properties (Akin et al., 2014; Galán and Lamas, 2019).

4. Validation

In this section, we assess the ability of the model to reproduce a number of key features observed in the data about the Spanish housing and mortgage markets. Following the macroeconomic agent-based modelling literature, we use three types of comparisons (Dawid et al., 2012; Ashraf et al., 2017; Popoyan et al., 2017; Fagiolo et al., 2019). First, we make sure the model captures the main patterns and stylised facts relevant to our research questions, such as house price cycles similar to those observed in reality. Second, we compare specific quantitative measures to make sure the model matches relevant moments, such as the amplitude of the cycles. Third, we focus also on the distribution of key variables for our study, such as those corresponding to the various mortgage risk metrics (loan-to-value, loan-to-income and debt-service-to-income ratios). For the sake of space, we show here only a selection of the whole range of validation checks performed.

An illustrative comparison of the house price cycles displayed by our model and those in reality is shown in Figure 3, where the cyclical component of the house price index (HPI) is plotted for both Spanish data and a single model run, representative of the usual output of the model. As can be seen in this figure, the model appears to capture the amplitude, frequency and general pattern of the cycles reasonably well. This resemblance is quantitatively confirmed in Table 1, where we show that both the amplitude and the period of the cycles generated by the model are very well in line with those observed in reality. Note that we measure the amplitude of the cycle with the standard deviation of the cyclical component of the house price index. It should also be noted that these cycles are completely endogenous, i.e., resulting from the actions and interactions of buyers and sellers in the market, and not related to any external input of shocks, as is generally required in other methodologies.

Variable	OECD Data	Model
Std. dev. of HPI (cyclical component)	0.4010	0.4028 ($\pm$0.0096)
Period of HPI (cyclical component)	201.0 months	202.45 months ($\pm$6.54)

Table 1: Comparison of model results with real data for the standard deviation and period of the cyclical component of the house price index (HPI). All model results are averages over 100 Monte Carlo simulations.

Three features are key for the emergence of realistic house price cycles in the model: *(i)* a feed-back loop between transaction and offer prices, *(ii)* trend-following household expectations, and

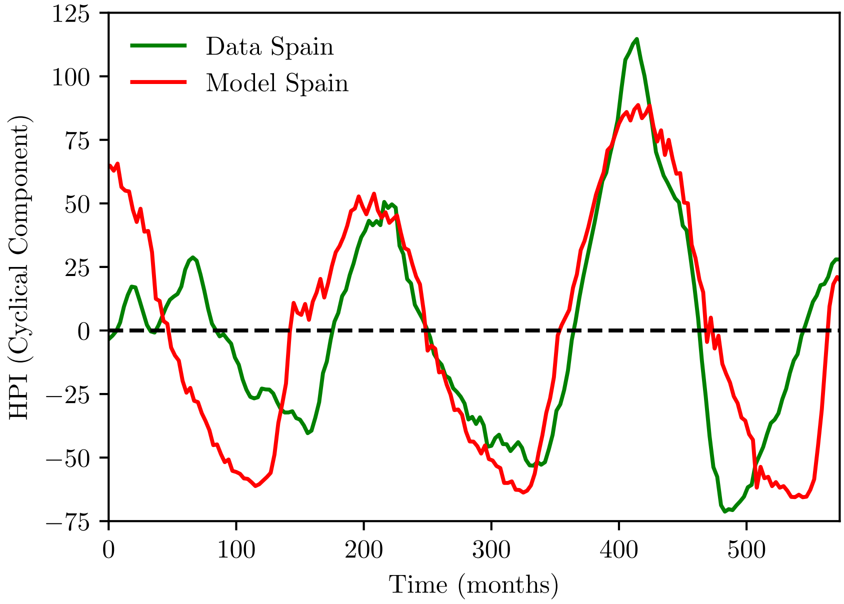

Figure 3: Comparison of model results with real data for the cyclical component of the house price index (HPI). All model results are averages over 100 Monte Carlo simulations. A Hodrick-Prescott filter with a smoothing parameter $\lambda = 129600$ has been applied to the data. Source: OECD real house price index data.

(iii) household heterogeneity.[10] The feedback loop between realised (past) transaction prices and those at which new sellers offer their properties in the market allows for the build-up of persistent price trends by accumulating price variations from month to month. Backward-looking, trend-following expectations regarding house price growth are key for creating momentum in the market, as they lead to an increase (decrease) in demand precisely when prices are already increasing (decreasing). Finally, income and wealth heterogeneity are essential for the emergence of strong cycles with realistic peak-to-trough amplitudes, as they make the pool of households who can potentially afford to buy progressively vary in size as prices change. Importantly, the range of prices these households can afford is strongly boosted by the availability of credit, and thus also tightly linked to the predominant lending standards. While not strictly necessary for the emergence of cycles, the existence of a dynamic buy-to-let sector also plays a relevant role in making them more realis-

[10] Importantly, if either of these factors is deactivated (for example, by modelling offer prices as independent of past sale prices, by setting the expected price growth to zero and by assigning all households the same income and propensity to save), the cycles completely disappear and the house price index behaves as small fluctuations around the mean.

tic. On the one hand, capital-gains-driven investors, who share the trend-following expectations of normal households, reinforce house price trends by seeking to acquire additional properties during the boom phase while they seek to decrease their portfolios during the contractionary phase. On the other hand, rental-income-driven investors arbitrate between the sales and the rental market, seeking to increase their portfolios when purchase prices are low relative to rental prices and vice versa.

In order to clarify the specific role played by these model features across the different phases of the cycle, we provide here a more detailed explanation of such a cycle. Let us first focus on the beginning of the expansionary phase, when prices start increasing, and thus so do the capital gains expected by households.[11] As a consequence of this increase in expectations, more and more households opt for a purchase instead of a rental bid, thereby increasing the demand in the ownership market. In terms of buy-to-let investing, this increase in expectations leads capital-gains-driven investors to choose to keep their properties and even try to acquire more, thereby increasing the demand and, at the same time, reducing the offer. Since the expansionary phase has just started and prices are still low, even rental-income-driven investors would seek to increase their portfolios to profit from attractive rental yields. As prices continue to rise, more constrained households (lower income, lower financial wealth) are progressively priced out of the market. However, for a while, there is still a large enough pool of less constrained households (higher income, higher financial wealth) able to bid and absorb the available houses on offer, thereby driving further price increases. In this way, we progressively move from a situation in which demand is sustained by the entire household sector to one in which demand is increasingly concentrated among wealthier households and buy-to-let investors. This underlines the relevance of household heterogeneity to sustain longer and stronger expansionary phases. However, as prices increase further, the pool of possible buyers (wealthy enough households) is so small that the resulting demand becomes unable to fully meet the available offer in the market. A further decrease in demand is due to rental-income-driven investors, as high purchase relative to rental prices make rental yields less attractive. As a consequence, a growing number of houses remain unsold on the market, experiencing progressive price drops as

[11] Note that this initial increase in prices might be arbitrarily small and due to either the heterogeneity among households or any of the stochastic components within the model dynamics. In any case, the mechanisms in the model will tend to strengthen this initially small price trend.

time advances and sellers slowly adapt to current demand levels. This leads to a reversal of the price trend, thereby initiating the contractionary phase of the cycle. As prices start dropping, households are more and more likely to decide to rent as opposed to buy, since they now expect purchases to lead to increasing capital losses. This same expectation of capital losses also drives capital-gains-driven investors to decrease their portfolios of properties, thereby both reducing the demand and increasing the offer in the ownership market. For a while, even if dropping prices are gradually making home-ownership more affordable, the expected capital losses are so large and the pool of unconstrained households still so small that the effective demand remains extremely weak. Finally, as prices decrease further and the pool of unconstrained households becomes large enough, even if the probability for each of them to choose to buy is still very low, since the number of trials is now sufficiently large, stochastically some of them will decide to buy. Furthermore, as purchase prices are now significantly lower while the demand in the rental market is still quite strong, high rental yields will drive rental-income-driven investors to increase their portfolios, thereby adding to the demand by non-investor households. In this way, the decreasing price trend will gradually moderate, eventually stop, and finally reverse, thereby triggering the beginning of a new cycle. Again, we note that household heterogeneity is crucial to sustain longer and deeper contractionary phases.

We further compare simulation results with the empirical distributions of the main mortgage risk metrics —loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios.[12] As can be observed in Figure 4, the model correctly captures such distributions, including not only their first moments, but also their general shape and, importantly, the upper tails of both the loan-to-income (LTI) and the debt-service-to-income (DSTI) distributions. This great match results from a complex interaction between the income distribution (exogenous), the house price distribution, the mortgage limits applied by the bank, the rent versus buy decisions of households, and their desired down-payments.

[12] Historically, the Spanish housing market has been prone to the over-appraisal of the value of transacted properties. As a consequence, at a given point in time, average appraisal values —which capture also expectations about the future evolution of prices— exceed average transaction prices (Akin et al., 2014; Galán and Lamas, 2019). For this reason, when comparing simulation results with Spanish data, we use loan-to-price ratios instead of loan-to-value ratios, as the former are more reliable and more directly comparable with the results of a model in which price is the metric of direct interest

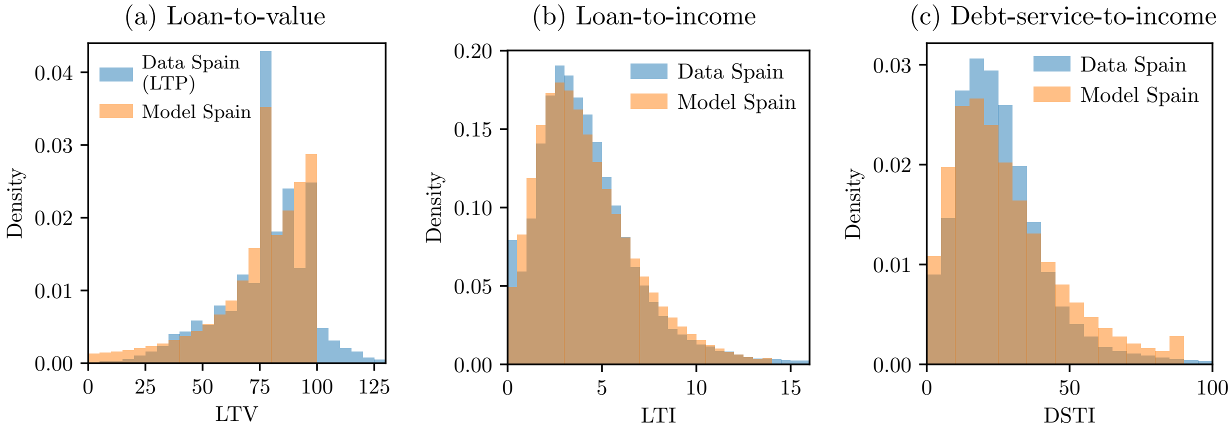

Figure 4: Comparison of model results with real data for the distributions of loan-to-value (LTV, note that loan-to-price, LTP, is used for data), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios. All model results are averages over 100 Monte Carlo simulations. Source: (LTP) Colegio de Registradores, 2016; (LTI) and (DSTI) European Data Warehouse, 2016.

Finally, let us focus in Figure 5 on a few stylised facts characterising several specificities of the Spanish housing market and portraying the broad range of empirical patterns our model is able to reproduce. First, the Spanish house-price-to-income distribution is characterised by a relatively long and heavy upper tail, with more than 20% of mortgages with ratios above 8 [see Panel (a)].[13] Second, the Spanish housing market has traditionally been characterised by a particularly high proportion of home-owners and a particularly small social housing sector [see Panel (b)]. Even if the proportion of home-owners has been progressively decreasing in recent years, it was still as high as 76% in 2016, our target calibration year. Third, the proportion of younger buyers among Spanish borrowers is extremely low, with less than 1.5% of borrowers below 25 years old, while the proportion of middle-aged buyers is relatively high, with more than 42% of borrowers between 35 and 44 years old [see Panel (c)]. Fourth, buy-to-let investment properties are fairly spread among small-scale landlords, with around 54% of investor households owning a single buy-to-let property and less than 7.6% of them owning 5 or more investment properties [see Panel (d)]. Summing up, our model successfully reproduces numerous and varied stylised facts characterising the Spanish housing market.

[13] It should be noted that, while income is exogenous in our model, both the decision to buy and the specific bidding and transaction prices paid by households are endogenous, and thus the house-price-to-income distribution

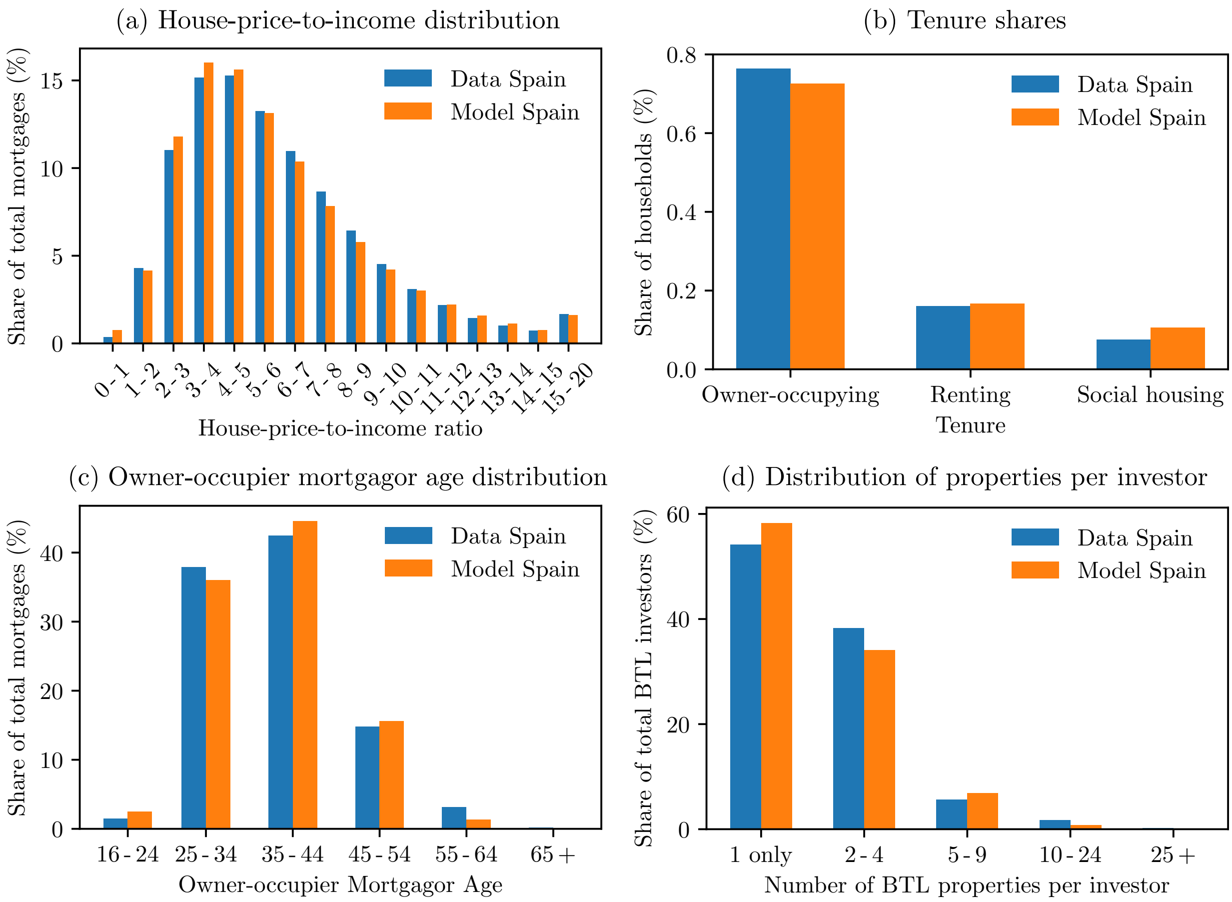

Figure 5: Comparison of model results with real data for key housing market variables. All model results are averages over 100 Monte Carlo simulations. Source: (a) and (c) European Data Warehouse, 2014-2020; (b) and (d) Encuesta Financiera de las Familias, 2017 wave.

5. Results

For the sake of the experiments to be presented below, we exploit the fact that this same methodology has already been successfully applied to the UK housing market. In fact, the UK is an ideal candidate to set as a benchmark for several reasons. First, it is similar enough to Spain to have cycles with a similar frequency and general shape. Second, its cycles are, however, significantly milder than the Spanish equivalent, particularly around the Global Financial Crisis. Finally, the availability of data for model calibration is better in the UK than in many other countries in Europe. We reproduce in Table 2 the results of the calibration to the UK (see also

is also an endogenous property of the model which cannot be simply attributed to the exogenous income distribution.

Carro et al., 2022), for comparison with the previously presented Table 1. In particular, note that the amplitude of the Spanish house price cycle is more than 17% larger than the UK equivalent.

Variable	OECD Data	Model
Std. dev. of HPI (cyclical component)	0.3424	0.3271 ($\pm$0.0304)
Period of HPI (cyclical component)	201.0 months	221.45 months ($\pm$18.53)

Table 2: Comparison of UK-calibrated model results with UK real data for the standard deviation and period of the cyclical component of the house price index (HPI). All model results are averages over 50 Monte Carlo simulations.

5.1. Exploring the drivers of house price cycle amplitude: hybrid parameterisations

In this subsection, we present the results of several experiments we have performed to quantify the effects of different model mechanisms on the amplitude of the resulting house price cycles. More specifically, on the one hand, we have shown above that the UK is characterised by a smaller house price cycle amplitude than Spain (see also Figure 1), and Carro et al. (2022) have shown that our model with a UK calibration is able to reproduce that smaller amplitude. On the other hand, we have shown in the previous section that the model with a calibration to Spain is able to reproduce the increased amplitude of the Spanish cycles. Thus, the question is: which aspects having changed between both calibrations are behind the increased amplitude of the Spanish cycles? To answer this question, we use a number of hybrid parameterisation of the model, that is, simulations mixing parameter values from multiple calibrations. In our case, we are interested in keeping most parameter values as those corresponding to the Spanish calibration, while testing the effects of switching one or just a few parameters to their UK calibration values. In this way, we can assess the effects of, for example, imposing the income distribution of the UK on an otherwise fully Spanish calibrated model.

Table 3 shows a summary of our results exploring the drivers of the house price cycle amplitude using hybrid parameterisation experiments. In particular, we notice that imposing on an otherwise Spanish calibrated model the UK distributions of income and wealth actually leads to stronger cycles. Switching parameters related to the desired bid price of households to their UK values leaves the amplitude of the cycles unchanged, while switching parameters related to their desired down-payments does lead to smaller cycles, but not enough to explain the full difference between the UK and Spain. On the contrary, by forcing the bank to draw mortgage characteristics from the

UK distributions of loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios whenever a household applies for a mortgage, we do observe important reductions of the amplitude of the cycles. In fact, in the three cases, the amplitude becomes even smaller than the actual UK value.

Specification	Std. dev. of HPI (cyclical component)
Spanish Data	0.4010
Full Spanish Parameterisation	0.4028
“ ” + UK Income Dist.	0.4922
“ ” + UK Wealth Dist.	0.4252
“ ” + UK Desired Bid Price	0.4018
“ ” + UK Desired Down-Payment	0.3766
“ ” + UK LTV Dist.	0.3160
“ ” + UK LTI Dist.	0.2757
“ ” + UK DSTI Dist.	0.2506
UK Data	0.3424

Table 3: Hybrid parameterisation results in terms of the standard deviation of the cyclical component of the house price index (HPI). All model results are averages over 100 Monte Carlo simulations. Source: OECD real house price index data.

The relevance of the distributions of LTV, LTI and DSTI ratios in leading to the strong Spanish house price cycle, as compared to the UK equivalent, is coherent with the important differences these distributions show between these two countries. Figure 6 shows these distributions both for the UK and for Spain. In particular, we can observe that, while the UK LTV distribution has its peak at a higher value than the Spanish equivalent distribution (90% vs 80%), the latter has far more mass above the peak (47% vs $<$ 5%). Furthermore, while the UK LTI distribution has almost no mass over 6, the Spanish equivalent distribution has around 20% of its mass over this value of 6. Equivalently, regarding DSTI ratios, the UK distribution has virtually no mass over 50 while the Spanish equivalent has around 7.5% of its mass over 50.

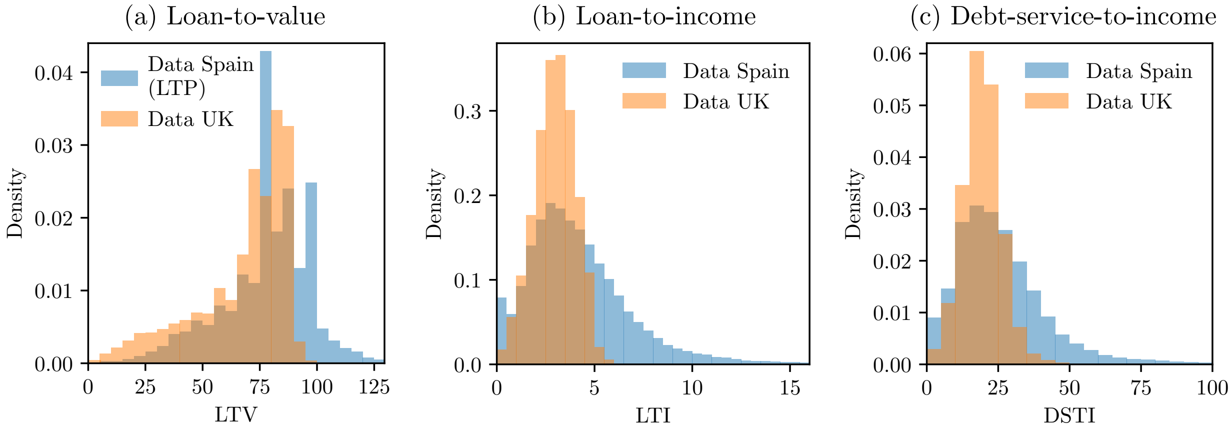

Figure 6: Comparison of Spanish and UK data for the distributions of loan-to-value (LTV, note that loan-to-price, LTP, is used for Spanish data), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios. Source: (LTP Spain) Colegio de Registradores, 2016; (LTI and DSTI Spain) European Data Warehouse, 2016; (LTV, LTI and DSTI UK) The Financial Conduct Authority's (FCA) loan-level Product Sales Data, 2011.

5.2. Calibration of borrower-based macroprudential policies

We present in Figure 7 results from two different calibration exercises: one with a hard loan-to-value (LTV) limit, i.e., with no mortgage allowed over the given limit, and the other one with a soft loan-to-income limit (LTI), i.e., with a certain fraction of mortgages (15%) allowed over the given limit. In both cases, the goal is to find the policy limit that would lead the Spanish house price cycle to match the amplitude of the UK equivalent. As before, the amplitude of the cycles is defined as the standard deviation of the cyclical component of the house price index. Also, in both cases, the x-axis represents the specific policy limit simulated while the y-axis represents the amplitude of the cycles obtained as a result.

As can be observed in Panel 7(a), a hard LTV limit of 94% makes the amplitude of the Spanish cycles equal to that of the UK cycles. Importantly, this value is larger than the natural limit (99th percentile) in the UK, which is 90%. Furthermore, note that this limit would have been binding for 21% of Spanish mortgages in 2016. Regarding the calibration of the soft LTI limit policy, shown in Panel 7(b), a limit of 4.77 applied to Spain would equate the amplitude of the cycles in both countries. Again, this value is slightly larger than the natural limit (99th percentile) in the UK, which is 4.5. Moreover, note that this limit would have been binding for 19% of Spanish mortgages in 2016, already taking into account the 15% allowance over the soft limit.

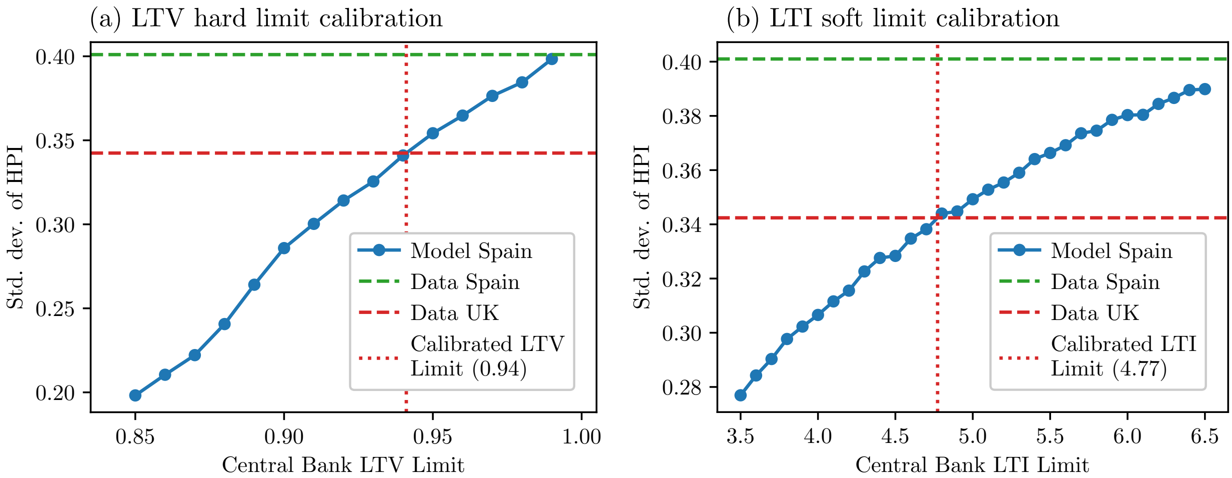

Figure 7: Calibration of an loan-to-value (LTV) hard limit and a loan-to-income (LTI) soft limit for the amplitude of the Spanish house price cycle to match that of the UK equivalent. All model results are averages over 100 Monte Carlo simulations. Source: OECD real house price index data.

5.3. Further effects of calibrated policies

In this subsection, we will analyse in more detail the effects of the policies calibrated in the previous subsection, including their effects on several distributions, on different types of households and over the different phases of the house price cycle.

Let us start with the effects of the calibrated policies on the distributions of mortgage risk metrics (loan-to-value, loan-to-income, debt-service-to-income ratios), shown in Figure 8, as well as their mean values, summarised in Table 4. The most important observation here is that policies targetting a given risk metric have an impact on other metrics. For instance, the loan-to-income (LTI) policy has a strong effect on the loan-to-value (LTV) distribution. In fact, this effect is even stronger than LTV cap, in the sense of leading to a smaller mean LTV ratio (see Table 4). Moreover, the LTV policy also leads to a significantly reduced tail of the LTI distribution. Finally, both policies have an impact on the DSTI distribution, though the impact of the LTI policy is certainly stronger.

We turn now our attention to the effects of the calibrated policies on the four stylised facts characterising specificities of the Spanish housing market as set out in Section 4, which are shown in Figure 9. As can be observed in Panel (a), both policies lead to a decrease of house-price-to-income ratios, with the share of mortgages falling for ratios above 5 and growing for ratios below 5. The LTI policy has a far stronger effect in this sense, almost 3 times stronger. Panel (b) shows

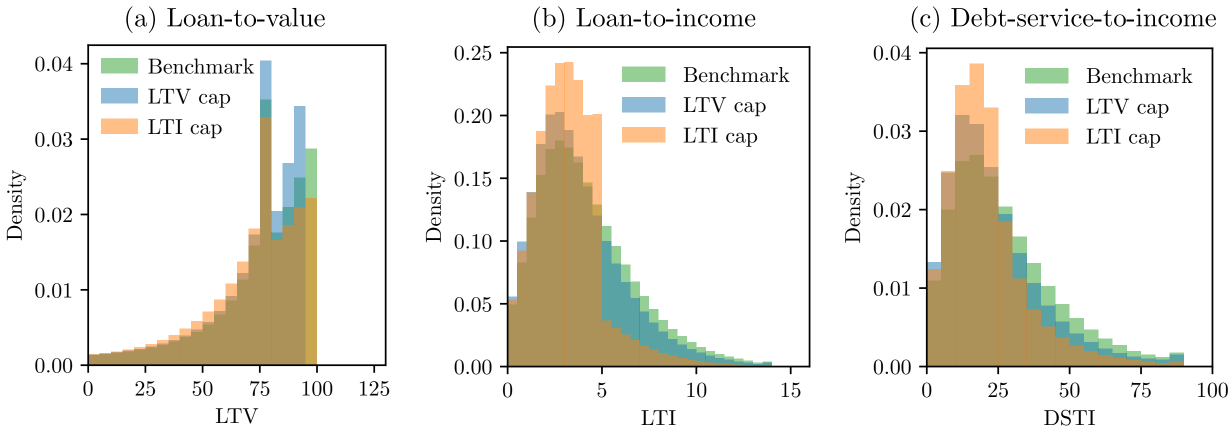

Figure 8: Impact of calibrated policies on the distributions of loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios.

Experiment	Mean LTV	Mean LTI	Mean DSTI
Benchmark	75.20	4.17	27.15
LTV cap	72.82	3.79	23.78
LTI cap	72.09	3.28	21.11

Table 4: Impact of calibrated policies on mean values of loan-to-value (LTV), loan-to-income (LTI) and debt-service-to-income (DSTI) ratios. All model results are averages over 100 Monte Carlo simulations.

that both policies lead to a decrease in home-ownership, replaced almost exclusively by private renting as opposed to social housing. This effect is twice as important with the LTV as with the LTI policy. As shown in Panel (c), the LTV policy leads to an increase in the share of older with respect to younger borrowers, while the LTI policy seems to have a negligible effect in terms of this age distribution. Finally, Panel (d) shows that both policies lead to an increase in the size of buy-to-let portfolios, with the share of single-property portfolios decreasing and the share of multi-property portfolios increasing. Here again, the impact of the LTV policy is almost twice as important as the impact of the LTI policy.

Using a Hodrick-Prescott filter to find the trend component of the house price index, we can divide each cycle into two different phases: an expansionary or boom phase, with an increasing price trend, and a contractionary or bust phase, with a decreasing price trend. In this way, for any variable of interest, we can compute two means by conditioning on the phase of the cycle, apart

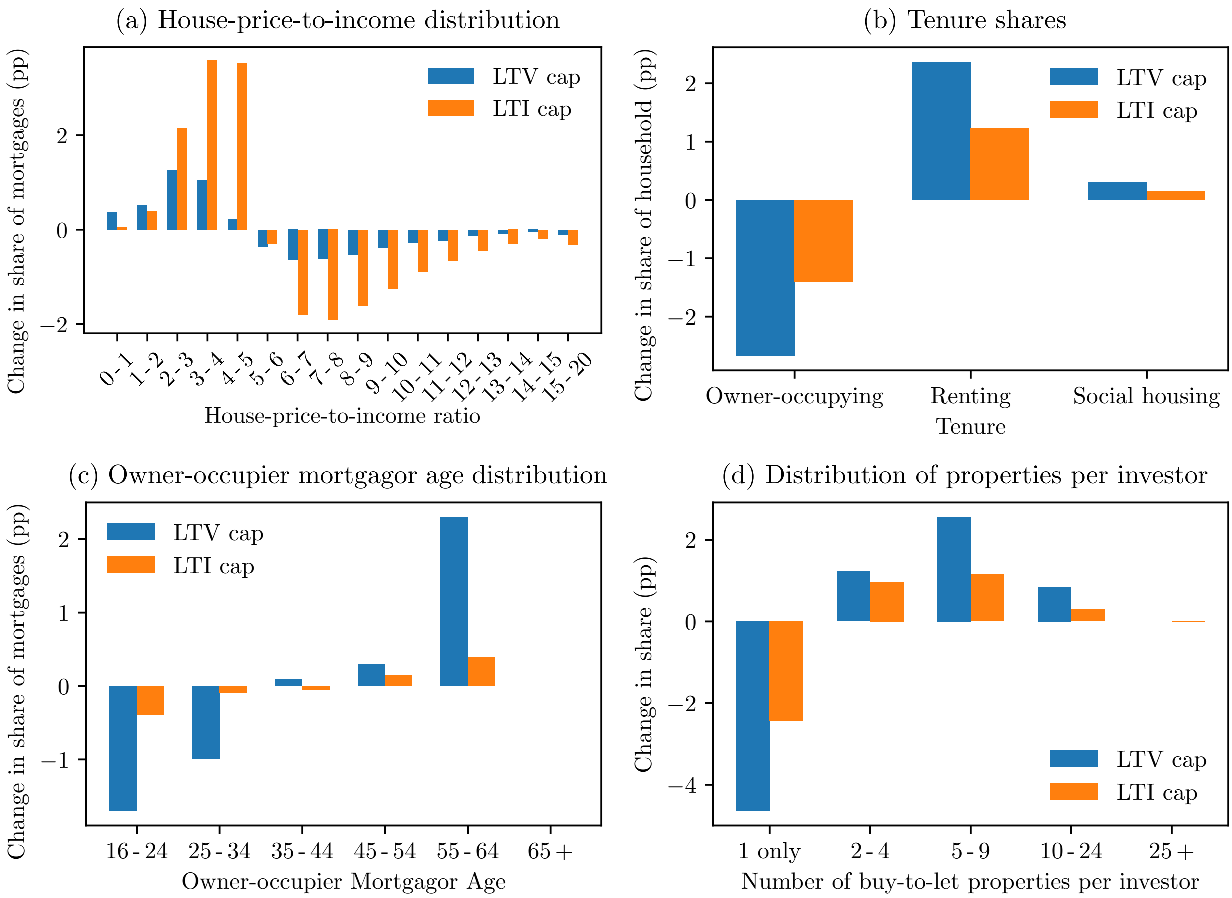

Figure 9: Impact of calibrated policies on key housing market variables. All model results are averages over 100 Monte Carlo simulations.

from the usual aggregate mean. Over the following figures, we will show the change or deviation from the no-policy benchmark in these three types of means for several key variables as a result of applying the two calibrated policies.

Figure 10 displays this deviation from the no-policy benchmark for the monthly credit growth, in Panel (a), and the monthly price growth, in Panel (b). There, we can observe that both policies lead to a strong reduction of credit and price growth during the expansionary phase and to an equivalently strong reduction of their decline during the contractionary phase. Interestingly, while the effect on price growth seems to be the same for both policies, the effect on credit growth is larger with the LTI policy. In other words, while the price cycle has, by calibration of our policies, the same amplitude for both of them, the LTI policy leads to a smoother credit cycle, as measured by month-to-month credit growth. This is a consequence of the fact that, while the LTI policy is binding for both first-time buyers and home movers, the LTV policy is restrictive mostly for first-time buyers (see Figure 11), thereby leaving some leeway for home movers to increase or decrease their demand for credit throughout the cycle. Finally, it is important to note that, in the aggregate, i.e., on average over both cycle phases, policies seem to have no effect either on credit or price growth.

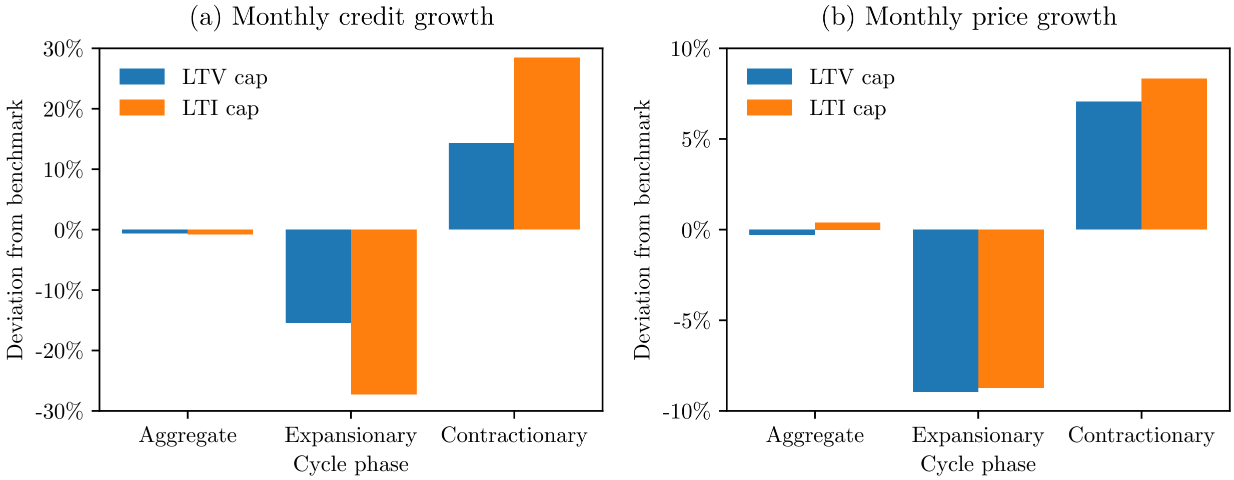

Figure 10: Impact of calibrated policies on credit and price growth over the cycle. All model results are averages over 100 Monte Carlo simulations.

Figure 11 shows the effect of both calibrated policies over the two phases of the house price cycle for the total monthly number of new mortgage approvals, as well as this number disaggregating by buyer type into mortgages for first-time buyers, home-movers and buy-to-let investors. In Panel (a) we can see that, while both policies lead to a slight decrease of total mortgage approvals in the aggregate, this decrease only affects the expansionary phase, mortgage approvals actually increasing during the bust phase. Finally, by comparing Panels (b), (c) and (d), respectively for first-time buyers, home-movers and buy-to-let investors, we can observe a strong shift in credit supply with the LTV policy from first-time buyers —decreasing mostly during the expansionary phase— to buy-to-let investors —increasing mostly during the contractionary phase. The LTI policy has a similar effect, but the impact in this case is observed for both first-time buyers and home movers, with both types of households experiencing a decrease in credit during the expansionary phase, again counterbalanced by an important increase in credit to buy-to-let investors during the contractionary phase.

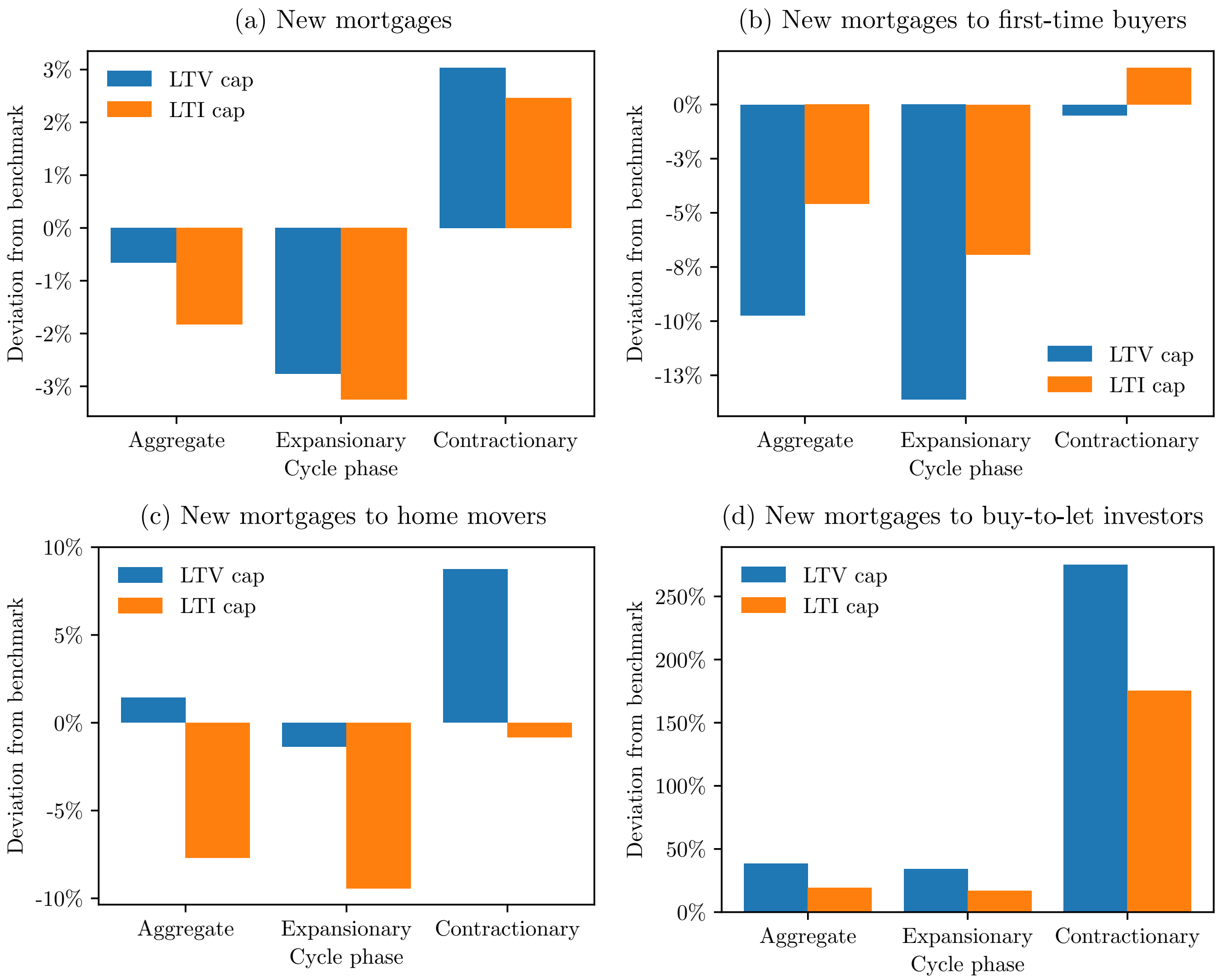

Figure 11: Impact of calibrated policies on lending to different types of households over the cycle. All model results are averages over 100 Monte Carlo simulations.

Two main mechanisms are responsible for this shift in credit. On the one hand, buy-to-let investors are generally characterised by a higher level of wealth and income, and are therefore less constrained by the policies under consideration. Our model captures this mechanism via the probability for a household to receive the buy-to-let flag, which depends on its income percentile as estimated from data. On the other hand, by moving constrained households from the sales to the rental market, both policies lead to a decrease in purchase prices, together with an increase in the demand for rental accommodation and therefore rental prices. In this way, a higher expected stream of rental income combines with a lower purchase cost to make buy-to-let investing more attractive to potential investors.

Interestingly, this strong shift in credit —and thus also in property ownership— towards buy-to-let investors translates only into a small increase in wealth inequality in the system.[14] In particular, the corresponding Gini coefficient increases only by 1.6% with the LTV policy and only by 0.2% with the LTI policy. This is due to the fact that, while buy-to-let investors do indeed own a larger share of the housing stock under the policies (specifically, 13.54% larger with the LTV policy and 4.65% larger with the LTI policy), since both of them lead, on average, to lower housing prices, the value of what these households own does not grow much with respect to the benchmark case. Furthermore, also as a consequence of lower housing prices, wealth differences between homeowners and non-homeowners are also smaller. Thus, the higher concentration of property under the policies is mostly counterbalanced by the smaller value of that property.

6. Conclusion

We have adapted, calibrated and validated for Spain an agent-based housing market model with endogenous house price cycles originally developed for the UK. This model includes life cycle dynamics, agent heterogeneity across multiple dimensions, heuristic rules of behaviour with adaptive expectations, both a sales and a rental market, and a dynamic buy-to-let sector. Exploiting the availability of these two parallel calibrations for two countries characterised by cycles of different amplitude, we have shown the prominent role played by the distributions of several mortgage risk metrics (loan-to-value, loan-to-income, debt-service-to-income), as well as desired down-payment mechanism, in leading to the observed larger amplitude of the Spanish house price cycle. We have used the model to calibrate both a hard loan-to-value (LTV) limit and a soft loan-to-income (LTI) limit —allowing for a certain fraction of mortgages over this limit— to smooth the Spanish house price cycle and match the amplitude of the UK equivalent. Importantly, both calibrated limits are less restrictive than the UK distributions would suggest. We have shown that both policies reduce credit and price growth during the expansionary phase, while they reduce their decline during the contractionary phase. In particular, the LTI policy was found to have a stronger effect on credit

[14] For the purpose of this analysis on wealth inequality, we use total net wealth, defined for each household as the sum of its financial wealth and its net housing wealth. Likewise, net housing wealth is defined as the mark-to-market value of the properties owned by the household —taking into account the specific quality segments they belong to— minus any mortgage debt owed by the household on these properties.

growth (15%) than the LTV policy, their impact on house price growth being equivalent. Finally, we have also uncovered a spillover to the buy-to-let sector, as both policies lead to a compositional shift in lending towards buy-to-let investors, the LTV policy from first-time buyers and the LTI policy from both first-time buyers and home-movers.

From a policy point of view, our work has several implications. First, we contribute a novel calibration exercise for borrower-based instruments in which we take a given amplitude of the house price cycle as a target, thereby explicitly focusing on the macroprudential policy goal of moderating house price fluctuations. Second, by using the amplitude of the UK cycle as a target in our policy calibration for Spain, we show that the calibrated limits might be less restrictive than the corresponding UK distributions would suggest. For instance, by focusing on the UK LTV distribution, one could naively assume that an LTV cap of 90%, corresponding to its 99th percentile, would be required to match its house price cycle amplitude. On the contrary, our calibration exercise suggests that a higher limit of 94% would be enough for the Spanish cycle to match the amplitude of the UK equivalent. This is a consequence of the fact that, among the many aspects that change between the two calibrations, some tend to make cycles softer while others tend to make them stronger. In other words, by fully calibrating the model to two different countries, our simulated policies are not applied in a neutral setting, but rather in two economies characterised by two specific and different combination of dampening and enhancing factors, and thus different policy limits might be required to attain the same effect. Importantly, this underlines the relevance of carefully calibrating models used for policy analysis to the country under consideration in order to obtain quantitatively meaningful policy limits. Third, as found by Carro et al. (2022), our results show that a policy targeting a specific risk metric can also have an important impact on other risk metrics. In fact, we find our calibrated LTI policy to have a stronger impact on the mean LTV than our calibrated LTV policy itself. This is an important effect that should be taken into account when calibrating any given policy to achieve a certain overall reduction in risk. Fourth, we find that the calibrated policies affect different types of households differently. In particular, we identify a shift in credit towards buy-to-let investors in substitution of first-time buyers (for both policies) and home-movers (for the LTI policy).[15] As the policies prevent some households

[15] Note that our results go beyond the analysis by Carro et al. (2022), whose simulated policies explicitly excluded buy-to-let investors. In our case, all households are subject to the simulated policies, and yet they are still affected

from securing mortgages large enough to purchase properties, there is a drop in demand in the ownership market and a corresponding increase in demand in the rental market. This, in turn, increases rental yields, thereby encouraging buy-to-let investors to increase their portfolios, which partially counterbalances the movements in demand in both markets. In this way, purchase prices do not drop by as much as they would without the intervention of buy-to-let investors, as part of the offer previously acquired by non-investor households is now hoarded by buy-to-let investors, who take advantage of the rise in rental yields to increase their portfolios. As a consequence, for most of the households initially prevented from buying by the implementation of the policy, the resulting decrease in purchase prices would not suffice for them to afford to buy under the new lending limits. Again, it is of paramount importance that these distributional effects and spillovers are taken into account in the design and calibration of macroprudential policies.

A caveat of the analysis presented here is the lack of a macroeconomic framework, which prevents us from exploring possible effects of macroprudential policies on the wider economy. To solve this, the housing model could be embedded into an agent-based macroeconomic model with a dynamic production sector.[16] This would make income endogenous and allow for unemployment shocks to arise from the interaction of the consumption and production decisions of the households and firms in the model. Moreover, it would allow to incorporate the production of houses as one more sector in the economy. A possible further improvement of our model would be to consider a more detailed banking sector. For instance, one could allow for dynamic lending standards, responsive to the phase of the house price cycle, as implemented by Tarne et al. (2021), or even to the quality of the bank's mortgage portfolio. Another example would be to include heterogeneous banks with different risk-taking behaviour and, as a consequence, different balance sheet structure. Finally, expanding the model in these two directions —adding macroeconomic features and considering a more detailed banking sector— would provide us with an ideal framework in which to study the impact of macroprudential capital buffers. Importantly, such a framework would allow not only to compare borrower-based with capital-based measures, but also to explore their

differently.

[16] The most relevant examples of macroeconomic agent-based models are the works by Dosi et al. (2010), Delli Gatti et al. (2011), Caiani et al. (2016), Seppecher et al. (2018), Ashraf et al. (2017), Cincotti et al. (2012), Dawid et al. (2014) and Mandel et al. (2010). See also the overview article by Dawid and Delli Gatti (2018).

interactions when applied in combination.

Appendix A Main model heuristics

In this appendix, we briefly review the main heuristics used by the agents in the model. For a more in-depth description of these rules of behaviour, we refer the reader to Carro et al. (2022). The model code can be downloaded from https://github.com/adrian-carro/housing-model-spain. Furthermore, the values of all mentioned parameters can be found in Appendix B.

Non-housing consumption

Since the model does not include a production sector, the only role of non-housing consumption is to determine the households' financial wealth, which will then influence their down-payments and thereby also the mortgages available to them. We consider two components of non-housing consumption: an essential or unavoidable component, modelled as a fixed nominal amount setting a minimum possible level of consumption, and a non-essential or desired component, modelled such that it leads to an accurate distribution of wealth. In order to model the desired component, we first define the target or desired level of financial wealth for a given household, w_{t}, as the inverse cumulative distribution of financial wealth conditional on gross income analysed at the household's propensity to save. Then, we define its desired consumption C as

$$C = \min\left(\max\left(\frac{1}{2}\left(w - w_{\mathrm{t}} + y_{\mathrm{d}}\right),\ 0\right),\ C_{\max}\right), \tag{1}$$

where y_{d} is the household's current monthly disposable income (i.e., after subtracting essential non-housing consumption and housing expenses), w is its current financial wealth (after adding this month's disposable income), and $C_{\max}$ is a maximum level of monthly desired consumption, defined as a fraction of the household's gross annual income.[17]

Desired purchase and rental bid prices

In terms of purchase bids, the desired purchase price p_d is modelled as an exponentially noisy and nonlinear function of the household's annual income y, with a cap imposed by the price

[17] This functional form ensures that *(i)* consumption is never negative, *(ii)* households with higher incomes consume more, *(iii)* financial wealth exponentially approaches its target level both from below and from above, and *(iv)* levels of financial wealth substantially above target do not lead to unrealistically high levels of consumption.

corresponding to the maximum mortgage the household could receive from the bank $p_{\max}$,

$$p_d = \min\Big(\alpha\ y^{\beta} e^{\varepsilon}\ ,\ p_{\max}\Big)\ , \tag{2}$$

where ε is a normal noise.[18] Regarding rental bids, similarly, we model the desired rental price r_d as a nonlinear function of the household's annual income y,

$$r_d = \min\Big(\mu\ y^{\nu}\ ,\ r_{\max}\Big)\ . \tag{3}$$

However, given that fluctuations in desired rental prices are far smaller than in desired purchase prices, we do not consider here an exponential noise as above. Finally, the desired rental price is capped by the maximum monthly payment the household could afford $r_{\max}$, given by its available income after subtracting essential non-housing consumption.

House price growth expectations

Households in our model are characterised by backward-looking, trend-following expectations regarding house price growth (Glaeser and Nathanson, 2017). Specifically, they use the (geometric) mean annual house price growth between the most recent quarter and the quarter γ years before as their expectation of annual growth in the future g,

$$g = \left(\frac{h_{t-1} + h_{t-2} + h_{t-3}}{h_{t-12\gamma-1} + h_{t-12\gamma-2} + h_{t-12\gamma-3}}\right)^{1/\gamma} - 1\,, \tag{4}$$

with γ being an independently calibrated parameter.

Buy vs rent decision

The choice between buying and renting is based on a cost comparison of both options (Gillingham, 1980).[19] In particular, once the household has decided on its desired purchase price p_d [see Eq. (2)], the annual cost of buying can be defined as the annual mortgage payments, $12\,m$, corresponding to the mortgage the household would require for such a purchase, minus the expected

[18] This functional form is inspired by Axtell et al. (2014). However, we do not consider a denominator dependent on the current price trend, as such a component did not meaningfully improve the estimation with our data.

[19] Note that, since in reality buy-to-let investors are generally also home-owners, we consider them to always choose to buy.

annual capital gains, $p_d\, g$, where g is the expected annual house price growth.[20] Regarding rental costs, households first find out the maximum quality Q that they can afford to buy given their desired purchase price and current market conditions, and then compute the annual rental cost as the exponential moving average annual rental price for a house of this quality Q under current rental market conditions, r_Q, multiplied by a factor $(1 + \lambda)$ representing a psychological cost of renting. Finally, we model the probability of choosing to buy, as opposed to rent, as a logistic function of the difference between their respective costs

$$P_{\text{buy}} = \sigma\Big(\theta\big[r_Q\,(1+\lambda) - \big(12m - p'_d\, g\big)\,\big]\Big)\,, \tag{5}$$

where θ is a sensitivity parameter and the logistic function is given by $\sigma(x) = 1/(1 + e^{-x})$.

Desired down-payments

If the financial wealth of the buyer is larger than the price of the house, then it will buy the house outright in cash; otherwise, it will apply for a mortgage.[21] Even though, in the latter case, the mortgage conditions set by the bank will include a minimum down-payment, the household can still decide to pay a larger initial deposit. In particular, we model desired down-payments by first-time buyers as their full financial wealth, since their savings are generally smaller, and thus they usually need to use most of them when buying a house. Regarding home movers and buy-to-let investors, we use two separate distributions estimated from data to derive their down-payments by analysing the corresponding inverse cumulative distribution at the household's income percentile.[22]

Home sale decision

The specific reasons leading households to sell their homes are beyond the scope of our model. Instead, we model home sale decisions as stochastic and leading to an estimated average holding

[20] Actually, for the purpose of this decision, we use a version of the household's desired purchase price capped by the exponential moving average sale price of houses of the maximum quality. This cap prevents households from using artificially large desired purchase prices, potentially detached from current market dynamics, when comparing with rental costs.

[21] This crude rule of behaviour is, however, quite successful in generating a roughly correct proportion of cash buyers.

[22] For coherence with current market conditions, we multiply down-payments by home movers and buy-to-let investors by the current house price index.

period of owner-occupied property of 13.3 years.[23]

Initial sale and rental offer prices

Whenever a household decides to sell a house of quality Q, whether its home or an investment property, it will offer it on the sales market at a price p_s given by

$$\ln p_s = \ln(\overline{p_Q}) + \eta\,, \tag{6}$$

where $\overline{p_Q}$ is the exponential moving average sale price of houses of the same quality Q and η is a random mark-up drawn from an estimated distribution of sale mark-ups. Similarly, an investor offering an investment property of quality Q on the rental market will do so for a monthly rent r_s given by

$$\ln r_s = \ln(\overline{r_Q}) + \eta\,, \tag{7}$$

where $\overline{r_Q}$ is the exponential moving average rent price of houses of the same quality Q and η is a random mark-up drawn from an estimated distribution of rental mark-ups.

Market bid-up mechanism

In either the sales or the rental market, whenever a house is matched with more than one bidder, the offer price is multiplied k times by a bid-up factor larger than 1 and estimated from data. The number of individual bid-ups k is drawn from a geometric distribution with a probability of success proportional to the number of bids received for this offer, such that the price of properties with more bidders increases more than the price of properties with fewer bidders. Specifically, this mechanism mimics a situation in which bids would arrive at random days during the month and a bid-up would take place each time a new bid arrives within a certain time window from the previous one, the bid-up process stopping otherwise.

Price reduction for unsuccessful sale and rental offers

Each month a house remains unsold on the sales market, with a certain probability estimated from data, its price is reduced according to

$$p_s^{t+1} = p_s^t \left(1 - \exp(\varepsilon)\right)\,, \tag{8}$$

[23] Note that, in order to prevent landlords from becoming homeless or even deciding to rent, homeowners with the buy-to-let flag never decide to sell their homes.

where t indicates the time step and ε is drawn from an estimated normal distribution.[24] Similarly, each month a house remains vacant on the rental market, with a certain probability, its price is reduced according to

$$p_r^{t+1} = p_r^t \left(1 - \exp(\varepsilon)\right) , \tag{9}$$

where ε is again drawn from a normal distribution. Both the reduction probability and the normal noise are, in this case, estimated from rental data.

Buy-to-let investment decisions

Each month, buy-to-let (BTL) investors decide whether to bid for a new investment property according to the probability $P_{\text{buy}}^{\text{BTL}}$, given by

$$P_{\text{buy}}^{\text{BTL}} = 1 - \big(1 - \sigma(\xi V_{\text{buy}})\big)^{\frac{1}{12}} , \tag{10}$$

where $\sigma(x)$ is the logistic function, ξ is a sensitivity parameter and V_{buy} is the expected yield of a hypothetical house maximising the leverage available to the household. Specifically, we model this expected yield as a weighted sum of both rental and capital yield rates multiplied by the corresponding leverage and subtracting the mortgage cost,

$$V_{\text{buy}} = \frac{p_{\max}}{d_{\min}} \big(\delta_i\, g + (1 - \delta_i)\overline{s} - \zeta\big) - \frac{12\, m_{\max}}{d_{\min}} , \tag{11}$$

where $p_{\max}$ is the price corresponding to the maximum mortgage available to the investor, $d_{\min}$ is the minimum down-payment the investor could make for such a mortgage, $12\, m_{\max}$ is the corresponding annual mortgage payment, $\overline{s}$ is the exponential moving average rental yield, g is the expected annual house price growth, δ_i is the weight given by the specific investor type i to capital gains as opposed to rental yield and ζ is an exogenous expected rate of return on alternative non-housing investments.[25] Similarly, for each investment property which is vacant or at the end of

[24] Note that, for houses with a mortgage, the seller withdraws the offer from the market if the price drops below the outstanding principal owed.

[25] Note that, since the model does not actually incorporate any explicit non-housing investment, the only role of this exogenous expected rate of return is to moderate the demand by buy-to-let investors when the expected rate of return on the housing investments they are considering is below this exogenous expected rate for non-housing investments.

its tenancy agreement, the buy-to-let owner decides whether to sell it according to the probability $P_{\text{sell}}^{\text{BTL}}$, given by

$$P_{\text{sell}}^{\text{BTL}} = 1 - \sigma(\xi V_{\text{sell}})^{\frac{1}{12}} \, , \tag{12}$$

where V_{sell} is the effective yield of the property under consideration. As before, this effective yield can be written as a weighted sum of both rental and capital yield rates multiplied by the leverage and subtracting the mortgage cost,

$$V_{\text{sell}} = \frac{\overline{p_Q}}{k}\big(\delta_i \, g + (1-\delta_i)s - \zeta\big) - \frac{12\, m}{k} \, , \tag{13}$$

where $\overline{p_Q}$ is the exponential average sale price of houses of the same quality, k is the current (mark-to-market) equity stake of the household in the house, s is the current (mark-to-market) rental yield of this specific property, g is the expected annual house price growth, δ_i is the weight given by the specific investor type i to capital gains as opposed to rental yield and ζ is an exogenous expected rate of return on alternative non-housing investments.

Bank lending standards

The bank offers two slightly different mortgage products depending on whether the intention is to owner-occupy the house or to use it as a buy-to-let investment property. Loans for owner-occupying are fixed-rate repayment mortgages with a default maturity of 25 years, which is reduced depending on the borrower's age in such a way that all principal is repaid by retirement age, as the bank assumes a strong drop in household income around that point. Loans for buy-to-let investing are also fixed-rate repayment mortgages, but always with a maturity of 25 years, as the bank assumes the future stream of rental income will be enough to cover mortgage payments. Both mortgage products are subject to the same three borrowing constraints, reflecting the bank's internal risk appetite or underwriting standards: *(i)* a soft loan-to-value (LTV) limit, allowing for a certain fraction of mortgages over it; *(ii)* a hard loan-to-income (LTI) limit; and *(iii)* a hard debt-service-to-income (DSTI) or affordability limit. Importantly, any lending regulation imposed by the Central Bank would only be binding if it is more constraining than these bank internal limits.

Mortgage interest rate

The interest rate paid by households on their mortgages is the sum of two contributions: a fixed policy rate exogenously set by the Central Bank and a variable spread endogenously set by the bank. The bank uses this interest rate spread to influence household demand for credit, with the goal of meeting a certain target of credit per household. In particular, we model interest rate spread movements as a linear function of movements of the amount of credit per household,

$$i_{t+1} = i_t + \varphi \frac{(C_t - C_{t-1})}{N}, \tag{14}$$

where i_t is the interest rate spread at time t, C_t is the total credit supply at time t (equivalent to credit demand in this model), N is the number of households and φ is a constant estimated from data.

Appendix B Estimation and calibration of model parameters

This appendix provides further information about the estimation and calibration of model parameters, as well as the underlying data sources used to this end. In particular, Subsection B.1 describes the main procedures used to set values for these parameters. Subsection B.2 lists all model parameters as well as their values and the procedures and data sources used for their estimation or calibration. Finally, Subsection B.3 explains the use of the method of simulated moments to calibrate the parameters which cannot be estimated nor postulated.

B.1 Types of parameteres by estimation or calibration procedure

Depending on the type of procedure used to set their value, the parameters of the model can be classified into four different categories:

1. User set parameters: These parameters are used either for general control of the model, such as the number of time steps to simulate, or to determine the policies in place in the different experiments, such as most Central Bank parameters. Regarding the latter, their default values are set as equal to those used by the private bank, such that they are not binding in the benchmark (no policy) case. They are only set to stricter, and thus binding, values for the purpose of policy experiments, such as the ones described in Section 5.

2. Estimated parameters: These parameters and distributions are directly estimated from available data sources. Most parameters in our model (34) belong to this category. Since some of the databases are only available for 2016, we set this year as our target for calibration, using always the closest possible year if data for 2016 are not available.

3. Postulated parameters with a sensitivity analysis: Due to the lack of data sources readily available to estimate these parameters, we have opted to postulate plausible values for them. This applies to 20 parameters in our model. In a few cases (13), these postulated values are based on the corresponding estimation made for the UK in Carro et al. (2022). Since the effects of these parameters are generally restricted to specific parts of the model or specific outputs, we perform an independent sensitivity analysis for each of them, instead of including them in our full calibration exercise.

4. Calibrated parameters: These parameters cannot be estimated from the available data sources for Spain, their effects are widespread across the model and its outputs and it is not clear how to postulate plausible values for them. In order to calibrate or find values for these parameters, we use the method of simulated moments. In particular, this applies to 5 parameters in our model.

B.2 Data sources and parameter values

After an initial table listing all of the data sources employed (see Table 5), as well as the acronyms used to identify them in the rest of this appendix, we report the full list of model parameters and their values arranged in a separate table for each model block (see Tables 6 to 14). Furthermore, for each parameter, the type of procedure used to set its value is also reported (see previous subsection), as well as the specific data sources involved. Regarding user set parameters, we report the values used in the no-policy benchmark simulation as an example. In the case of postulated parameters based on the corresponding estimation made for the UK in Carro et al. (2022), this latter work is cited as a data source. For calibrated parameters, further details are provided in Appendix B.3 about the specific calibration methodology used. Finally, for a more in-depth description of the role played by each parameter within the model, as well as further details about the estimation and calibration procedures used, we refer the reader to Carro et al. (2022).[26]

[26] While the estimation and calibration of model parameters in Carro et al. (2022) is exclusively focused on the UK, the methods used here for Spain are mostly analogous.

Acronym	Acronym Description
BdE	Banco de España
BdE-Indicadores	Indicadores del Mercado de la Vivienda (collected by BdE, 2014–2020)
CdR	Colegio de Registradores
CdR-Anuario	Anuario 2016 (collected by CdR, 2016)
CdR-Data	Transactions Micro-Data (collected by CdR, 2014–2021)
CIR	Central de Información de Riesgos (collected by BdE, 2014–2021)
ECH	Encuesta Continua de Hogares (collected by INE, 2016)
ECV	Encuesta de Condiciones de Vida (collected by INE, 2015–2017)
EDW	European Data Warehouse Securitisation Repository (2014–2020)
EFF	Encuesta Financiera de las Familias (collected by BdE, 2017)
EPA	Encuesta de Poblacion Activa (collected by INE, 2016)
INE	Instituto Nacional de Estadística
INE-Hipotecas	Estadísticas de Hipotecas (collected by INE, 2016)
MRO	Main Refinancing Operations rate set by the ECB

Table 5: List of data sources

Parameter	Value
Seed for random number generation	1
Number of time steps	5,000
Number of simulations	100
Number of households	10,000
Time step to start recording transactions	1,000
Rolling window for core indicator averages (in months)	6
Cumulative weight for events beyond 12 months	0.25

Table 6: General user set parameters (no-policy benchmark)

Parameter	Value	Source
Hard maximum LTV ratio	0.9999	-
Soft maximum LTI ratio	15.0	-
Hard maximum DSTI ratio	0.9999	-
Exogenous policy rate	0.0%	MRO [a]
Policy application time	500	-

[a] Rate set by the ECB since 16/03/2016 till 27/07/2022.

Table 7: Central Bank user set parameters (no-policy benchmark)

Parameter	Equation	Value	Source
Number of households	(14)	$N = 18,444,200$	EPA [a]
Number of dwellings	-	$16,694,333$	ECV, ECH [b]

[a] Average of the 4 quarters in 2016. [b] Fraction of owner-occupying or privately renting households (ECV, average for 2015-2017) multiplied by the total number of households (ECH, 2016).

Table 8: Initial model set-up parameters

Parameter	Equation	Value	Source
Age	-	Estimated distribution	EFF
Gross income	-	Estimated distribution	EFF [a]
Financial wealth	(1)	Estimated distribution	EFF [b]
Essential non-housing consumption	-	200 €	EFF [c]
Maximum desired consumption fraction	(1)	0.1751	EFF [d]

[a] Distribution of gross income, defined as gross total income minus gross rental income, conditional on age.
[b] Distribution of net financial wealth, defined as financial assets minus outstanding unsecured debt, conditional on gross income. [c] 1^{st} percentile of monthly consumption values. [d] 99^{th} percentile of monthly consumption fractions over gross annual income, defined as gross total income minus gross rental income.

Table 9: Income, non-housing consumption and financial wealth parameters

Parameter	Equation	Value	Source
Desired purchase price			
Scale	(2)	$\alpha = 511.3222$	EDW [a]
Exponent	(2)	$\beta = 0.5559$	EDW [a]
Std. dev. of normal noise	(2)	$\varepsilon_\sigma = 0.3975$	EDW [a]
Desired rental price			
Scale	(3)	$\mu = 8.4359$	EFF [c]
Exponent	(3)	$\nu = 0.4098$	EFF [c]
House price growth expectations			
Time window	(4)	$\gamma = 4$ years	Postulated [b]
Psychological cost of renting	(5)	$\lambda = 0.8$	Calibrated
Rent vs purchase sensitivity	(5)	$\theta = 0.01$	Calibrated
Desired down-payments			
Scale	-	10.1804	CdR-Data
Shape	-	1.1138	CdR-Data

[a] Linear fit of logarithmic house prices as a function of logarithmic buyer household incomes, weighted by house prices. Data restricted to purchases between 2014 and 2020 and to household incomes within the 98% interpercentile range. [b] Integer values between 1 and 10 were tested in a sensitivity analysis, with 4 leading to the most realistic house price cycles (amplitude and period). [c] Linear fit of logarithmic rental prices as a function of logarithmic buyer household incomes, weighted by rental prices. Data restricted to household incomes within the 98% interpercentile range.

Table 10: Housing decisions if in social housing

Parameter	Equation	Value	Source
Holding period of owner-occupied houses	-	13.30 years	CdR-Anuario
Initial sale price mark-up, η	(6)	Estimated distribution	Postulated [a]
Sale price reduction			
Monthly probability	-	0.0703	Postulated [a]
Mean percentage reduction	-	1.4531	Postulated [a]
Std. dev. of percentage reduction	-	0.7070	Postulated [a]

[a] Same values as estimated by Carro et al. (2022) for the UK using Zoopla listings micro-data.

Table 11: Housing decisions as an owner-occupier

Parameter	Equation	Value	Source
Probability to receive buy-to-let flag			
Raw probability	-	Estimated dist.	EFF [a]
Probability adjustment	-	1.6	Calibrated
Buy-to-let motivations			
Rental-income-driven, probability	-	0.4927	Postulated [b]
Rental-income-driven (RI), weight	(11) and (13)	$\delta_{\mathrm{RI}} = 0.1$	Postulated [c]
Capital-gains-driven, probability	-	0.1458	Postulated [b]
Capital-gains-driven (CG), weight	(11) and (13)	$\delta_{\mathrm{CG}} = 0.9$	Postulated [d]
Mixed, probability	-	0.3615	Postulated [b]
Mixed (M), weight	(11) and (13)	$\delta_{\mathrm{M}} = 0.5$	Postulated [e]
Expected non-housing rate of return	(11) and (13)	$\zeta = 4.0755\%$	BdE-Indicadores [f]
Sensitivity of buy and sell decisions	(10) and (12)	$\xi = 100$	Calibrated
Desired down-payments			
Scale	-	10.2693	CIR
Shape	-	1.0061	CIR
Initial rent price mark-up, η	(7)	Estimated dist.	Postulated [g]
Rent price reduction			
Monthly probability	-	0.1057	Postulated [g]
Mean percentage reduction	-	1.6559	Postulated [g]
Std. dev. of percentage reduction	-	0.7855	Postulated [g]
Tenancy length			
Minimum	-	12 months	Postulated [h]
Maximum	-	36 months	Postulated [h]

[a] Probability per gross income percentile bin, gross income defined as gross total income minus gross rental income, buy-to-let households flagged by non-zero gross rental income. [b] Same values as estimated by Carro et al. (2022) for the UK using NMG/BoE survey data for 2014. [c] Chosen to represent a stylised rental-income-driven strategy while still putting some weight on capital gains to avoid unrealistic behaviours. [d] Chosen to represent a stylised capital-gains-driven strategy while still putting some weight on rental income to avoid unrealistic behaviours. [e] Chosen to represent a stylised strategy with equal weight on capital gains and rental income. [f] Average return on 10 years maturity public debt (secondary market) over the 5 years before our target calibration year (2010–2015). [g] Same values as estimated by Carro et al. (2022) for the UK using Zoopla listings micro-data and ONS aggregate rental data. [h] Standard minimum and maximum length of rental contracts as per regulation in force in 2016.

Table 12: Housing decisions as a BTL investor

Parameter	Equation	Value	Source
LTV ratio limits			
Soft maximum	-	0.9999	Postulated [a]
Hard maximum	-	0.8	CdR-Data [b]
Fraction over soft maximum	-	0.4699	CdR-Data [b]
LTI ratio limit, hard maximum	-	13.8266	EDW [c]
DSTI ratio limit, hard maximum	-	0.8974	EDW [c]
Mortgage duration	-	30 years	CdR-Data [d]
Minimum mortgage age	-	24 years	EDW [e]
Maximum mortgage age	-	61 years	EDW [e]
Bank initial interest rate	(14)	2.3536%	BdE-Indicadores
Bank initial credit supply per household	(14)	140.23 €	INE-Hipotecas, EPA [f]
Elasticity of interest rate to credit	(14)	$\varphi = 1.7839e^{-5}$	BdE-Indicadores, INE-Hipotecas, EPA [g]

[a] By construction, there can be no LTV ratio at or above 1.0 in the model. [b] Soft maximum limit chosen as the mode of the distribution. Note that the loan-to-price (LTP) rather than the loan-to-value (LTV) is used in the data, given its greater reliability in the presence of a historical tendency to over-appraise the value of transacted properties (Akin et al., 2014; Galán and Lamas, 2019) in the Spanish housing market. [c] Limit is set as the 99^{th} percentile of the corresponding distribution, with both primary and secondary (if available) borrower income taken into account when computing household income. Data restricted to purchases between 2014 and 2020. [d] Mode of the distribution. [e] 1^{st} and 99^{th} percentiles of the distribution. [f] Total amount of new mortgage credit for dwellings in 2016 (INE-Hipotecas), divided by the total number of households in that same year (EPA). [g] Interest rate differences (BdE-Indicadores) divided by total amount of new mortgage credit for dwellings per household differences (INE-Hipotecas, EPA).

Table 13: Bank parameters

Parameter	Equation	Value	Source
Distribution of house prices			
Scale	-	11.8929	CdR-Data
Shape	-	0.6366	CdR-Data
Distribution of rental prices			
Scale	-	5.9974	EFF
Shape	-	0.5905	EFF
Weight on market vs segment prices	-	0.7	Calibrated
Bid-up parameter	-	1.0746	Postulated [a]
Days under offer	-	3	Postulated [a]
Initial rental gross yield	-	4.4175%	BdE-Indicadores [b]

[a] Same values as estimated by Carro et al. (2022) for the UK using Zoopla listings micro-data.

[b] Average over the 4 quarters in 2016.

Table 14: Housing market parameters

B.3 Calibration: Method of simulated moments

After using available data sources to estimate as many parameters as possible, as well as postulating parameter values whenever data is missing but an informed guess together with a sensitivity analysis are enough, we are still left with 5 parameters requiring a calibration. To this end, we use the method of simulated moments (Gilli and Winker, 2003; Franke, 2009; Franke and Westerhoff, 2012; Fabretti, 2013; Chen and Lux, 2018; Platt and Gebbie, 2018). In particular, we first build an objective function that measures the distance or error between a set of simulated moments and their corresponding data equivalents. Then, we explore the parameter space by launching simulations with parameter values evenly distributed across the corresponding hypercube. By finding the minimum of the objective function over these simulations, we identify those parameters values which minimise the distance between the simulated moments and those estimated from data. Importantly, we ignore parameter combinations for which any of the simulated moments lies outside a bound of acceptability of ±25% from the corresponding target moment. This ensures being close enough to each of the moments selected, thus avoiding being too close in some and too far in others.

The parameters calibrated with this method, together with the specific values explored, are:

- Psychological cost of renting [see Eq. (5)]. Values explored: 0.0, 0.2, 0.4, 0.6, 0.8, 1.0.

- Rent vs purchase sensitivity [see Eq. (5)]. Values explored: 0.00001, 0.00003162, 0.0001, 0.0003162, 0.001, 0.003162, 0.01, 0.03162, 0.1.
- Buy-to-let probability adjustment. Values explored: 1.48, 1.52, 1.56, 1.6, 1.64, 1.68, 1.72, 1.76, 1.8.
- Sensitivity of buy-to-let buy and sell decisions [see Eqs. (10) and (12)]. Values explored: 0.1, 0.3162, 1, 3.162, 10, 31.62, 100, 316.2, 1000.
- Weight of market vs segment house prices. Values explored: 0.1, 0.3, 0.5, 0.7, 0.9.

Thus, we have explored 21870 parameter combinations, with 10 simulations per parameter combination, and with 5000 time steps per simulation, out of which the first 1000 time steps are always discarded. Finally, the moments used in building the objective function, as well as the specific values targeted and the simulation values resulting from the calibration, are shown in Table 15.

Moment	Target Value	Simulation Value
House Price Index (HPI) mean	1.0	0.9896
House Price Index (HPI) std. dev.	0.4010	0.4028
House Price Index (HPI) cycle period	201.0 months	202.45 months
Rental Price Index (RPI) mean	1.0	0.9511
Share of households owning	0.7753	0.7247
Share of households renting	0.1733	0.1687
Share of households buy-to-let investing	0.0781	0.0609
Rental yield mean	4.42%	3.85%
Interest rate spread mean	2.35%	2.47%

Table 15: Moments and their target values

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